Growth or Reallocation? The Impacts of Public Infrastructure on Local Business: The Case of EV Charging in Kansas City*

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Abstract

Public infrastructure investment improves local accessibility and the built environment, benefiting nearby businesses through two mechanisms: a net growth effect that attracts consumer visits that would otherwise not occur, and a redistributive effect that shifts consumer choices away from competing locations without increasing aggregate spending. We study these effects through a case study of the deployment of public electric vehicle (EV) charging stations in Kansas City. Using granular mobile-device tracking data and a random-coefficients discrete choice model with instrumental variables for endogenous placement of charging stations and travel costs, we find that consumers' restaurant choices exhibit a substantial willingness-to-pay for proximity to charging infrastructure, equivalent to 180 percent of their baseline trip cost. We estimate that nearby EV charging stations, on average, raise a restaurant's market share by 20 to 28 percent, in which roughly one-quarter comes from consumers substituting away from local competitors. The study highlights that neglecting the redistributive channel leads to overestimation of the local economic returns to public infrastructure investment.

*All errors are our own.

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1 Introduction

Public infrastructure fundamentally shapes the spatial distribution of consumer behaviors and local economic activities. Many studies on evaluating the economic impact of public infrastructure assume that all estimated business gains from infrastructure improvements represent a net increase in overall economic activity. This assumption conflates two conceptually different mechanisms: a net growth effect, driven by reductions in travel efforts and improvements in visiting experience that attract consumer visits that would otherwise not occur, and a redistributive effect, driven by spatial substitution such that consumers divert their existing spending from other local competitors. Failure to distinguish and disentangle the two mechanisms overstates the aggregate economic returns to public infrastructure investment and risks misguiding cost–benefit analyses underlying public investment decisions. While many large-scale public infrastructure investments in the United States are drawn from dated contexts, such as the expansion of the interstate highway system in the 1970s and airports and aviation infrastructure in the 1980s, the recent trend toward transportation electrification, driven by the widespread adoption of electric vehicles (EVs), offers a timely natural empirical setting to study the distributional effects of infrastructure improvement on local economic activities. Charging stations may attract increased consumer visits and catalyze commercial revitalization of the surrounding area not only by providing charging services, but more importantly by enhancing the overall visitation experience through multiple channels such as signaling neighborhood modernization and improving perceived safety and amenity. Because mobile-device visit data could hardly provide identification of individual vehicle ownership, we study the aggregate effect of charging infrastructure on restaurant visits—encompassing all of these channels simultaneously—rather than isolating the contribution of EV drivers specifically.

This paper asks two related questions. First, does proximity to public EV charging infrastructure measurably change consumer dining choices and increase restaurant visits, due to improvement in the local built environment? Second, what are the heterogeneous welfare and distributional consequences—both for consumers and across competing establishments—of this infrastructure? To answer these questions, we prepare a dataset of mobile-device visit records for the Kansas City metropolitan area in 2019, matched to the dataset of public EV charging stations available at the same time period. We bring this data to a random-coefficients discrete choice model following S. Berry, Levinsohn, and Pakes (1995), estimated using instrumental variables (IVs) to address two sources of endogeneity. The first endogeneity source is from the supply side: in 2019, public EV charging in Kansas City was driven largely by publicly subsidized programs with explicit equity mandates to target historically underinvested and less commercially developed neighborhoods, creating a negative correlation between charging presence and the commercial quality of surrounding establishments and biasing OLS estimates downward. The second endogeneity source is from the demand-side: as documented by Bradt (2025), residential sorting around preferred destinations causes standard distance measures to understate the true disutility of travel, biasing the travel-cost coefficient toward zero and inflating implied willingness-to-pay. We address both concerns using three families of IVs: (i) following spirit of Faber (2014) to simulate charging networks constructed from predetermined geographic features such as road

and population density grids; (ii) future peripheral charging deployment occurring at least six months after our sample period; and (iii) external oil-market shocks that shift per-mile travel costs without directly influencing restaurant quality.

Our model and analysis yield three important findings. First, charging infrastructure has a large causal effect on restaurant visits, raising surrounding restaurants' market share by 20–28 percent. Second, consumers place considerable value on nearby charging access, with willingness-to-pay equivalent to 180 percent of their baseline trip cost. Third, a significant portion of the estimated business gains is redistributive rather than additive: roughly one-quarter of the visit increase comes from consumers substituting away from local competitors. In other words, although an individual restaurant near a charger on average enjoys a 28.5 percent visit boost, if chargers were deployed to all restaurants, the average visit increase per restaurant would be only about 20.6 percent. In terms of the net growth effect, we estimate that as of 2019, the existing charging network has increased city-wide restaurant visits by 8–9 percent, and extending the charging station network to all restaurants would raise consumer visits by a further 13 percent beyond the current baseline.

This paper is among the few to study how EV charging infrastructure shapes consumer choices at the level of individual competing businesses, building on Zheng, Keith, Wang, Diao, and Zhao (2024), who document positive reduced-form spending effects of charging stations on nearby establishments in California. We go further by estimating a structural demand model that recovers consumer willingness-to-pay and allows counterfactual welfare analysis, and highlighting the competitive distribution that shows a significant share of establishments' gain comes from substitution from local competitors. This distinction between gross and net effects has direct implications for how infrastructure policies should be better designed.

The remainder of the paper proceeds as follows. Section 2 provides background on EV charging and related literature. Section 3 describes the data. Section 4 presents the demand model. Section 5 discusses identification and estimation. Section 6 presents main results and robustness. Section 7 reports counterfactual policy exercises. Section 8 summarizes the paper.

2 Background and Related Literature

2.1 EV Adoption and Destination Charging

Electric vehicle adoption in the United States accelerated substantially after 2015, driven by expanding model availability, and a combination of federal and state incentives. By 2019—our sample year—EVs represented a small but rapidly growing fraction of new vehicle registrations, with concentrations in metropolitan areas that also tend to have the higher restaurant density and the more developed charging networks.

A critical feature of EV technology is charging time. Level 2 AC chargers, which constitute the majority of public infrastructure at commercial locations, deliver roughly 10–25 miles of range per hour. Drivers who plan to charge at a destination can absorb charging

time within the duration of the business visit, creating a potential complementarity between destination charging and business visits. However, because our visit data does not allow us to identify individual vehicle type, we cannot isolate this channel empirically. The effects we estimate are therefore best interpreted as the aggregate impact of charging infrastructure on the local built environment— capturing EV-driver complementarities alongside broader amenity and signaling effects—rather than as estimates of a specific EV-driver mechanism.

From the business perspective, proximity to a charger may serve as a signal of quality, environmental commitment, or neighborhood investment, and may attract customers who value co-location with charging infrastructure regardless of vehicle ownership. These amenity and signaling effects are distinct from—and empirically inseparable from— EV-specific dwell-time complementarities in our data.

The Kansas City metropolitan area is an informative setting for studying these effects. It spans two states (Missouri and Kansas) with distinct policy environments, encompasses dense urban cores, established suburbs, and dispersed rural communities, and had an active public charging network in 2019 supported by a combination of private operators (ChargePoint, Blink, EVgo) and publicly subsidized installations under the Volkswagen Dieselgate settlement environmental mitigation fund.

2.2 Related Literature

This paper connects to several strand of literature. First, we relate to work on how physical infrastructure shapes consumer behavior and business performance, while emphasizing the distinction between net growth and spatial reallocation effects. Faber (2014) provides a canonical example, using a hypothetical network based on geographic cost minimization as an instrument for highway access in China. Our simulated-network instruments for charging availability are designed in the same spirit, exploiting variation in geographic suitability for charging deployment rather than actual deployment decisions. We show that a substantial share of these gains reflects spatial reallocation across competing establishments rather than new economic activity.

Second, the paper contributes to the discrete-choice demand literature. Our framework builds directly on S. Berry et al. (1995) and its practitioner guide by Nevo (2000). While BLP-style models have been widely applied to retail and location choice settings, existing work typically treats amenities as fixed or exogenous. Related work such as Bradt (2025) highlights the endogeneity of distance and location attributes in such settings. our contribution is to treat a complementary infrastructure amenity—charging access—as an endogenous product characteristic of the dining location rather than an intrinsic restaurant attribute. We allow charging access to enter utility while also affecting substitution patterns across locations through travel cost and spatial proximity, and we instrument for its placement using simulated network variation.

Third, the paper relates to work on EV infrastructure. Springel (2021) estimates the demand for EVs in Norway as a function of charging network density, finding significant network externalities. S. Li, Xiao, and Liu (2017) uses a discrete-choice model to study EV adoption in China. Our paper differs from both in focusing on the downstream effects of

charging infrastructure on non-EV businesses. Using high-frequency mobility data at the restaurant–market level, we estimate how charging infrastructure affects consumer choice across restaurants and recover willingness-to-pay for proximity to charging, capturing both direct and indirect channels even when individual vehicle ownership is unobserved.

Finally, our counterfactual analysis links to the industrial organization literature on local competition and spatial differentiation. Built on Seim (2006), we quantify the gap between private and social returns to infrastructure investment.

3 Empirical Setting and Measurement

3.1 Empirical Setting and Data

Our primary data are mobile-device location records for the Kansas City Designated Market Area (DMA) throughout 2019, sourced from Cuebiq. The Kansas City DMA serves as an attractive empirical setting for studying infrastructure spillovers on local business activity. Its population size and demographic composition are broadly representative of mid-sized American markets. Its relative geographic isolation from other major urban centers minimizes the confounding influence of interstate corridor charging, where the primary purpose of a stop is long-distance travel replenishment rather than local destination activity. And its low exposure to external tourism means that restaurant foot traffic is driven primarily by local residents, keeping the analysis focused on the spatial reallocation of consumer activity within the market rather than aggregate demand shocks from outside.

The Cuebiq dataset tracks these anonymized device movements at a fine spatial resolution. A device is classified as visiting a restaurant if it is detected within the establishment's geographic footprint and remains for between 30 and 120 minutes, thresholds calibrated to match typical dining durations while excluding brief pass-throughs and extended stays inconsistent with dining. Devices are attributed to a home census tract, which serves as the population-group identifier.

We observe visits to restaurants in the Kansas City DMA drawn from a commercial points-of-interest universe matched to physical addresses and geographic coordinates. We retain restaurants with stable representation across the sample period, yielding a panel of over a thousand distinct establishments over 12 monthly periods.

3.2 Market Definition and Share Construction

A market is defined by the interaction of a calendar month t and a population group (census tract) g: $m \equiv (t, g)$. This definition captures variation on both the demand side (tract-level demographics and travel patterns) and the supply side (month-by-month evolution of the charging network as new stations come online).

Market shares require a denominator: the total number of potential dining occasions from tract g in month t. We construct this using a device-availability approach. A device contributes a potential dining occasion to market (t, g) if it is resident in tract g, is observed

online during the dinner window (6:00–10:00 pm) in month t, and is observed to dwell at a single location for between 30 and 120 minutes during that window. The inside-option share of restaurant j in market m is:

$$s_{jmt} = \frac{\text{visits from tract } g \text{ to restaurant } j \text{ in month } t}{\text{potential dining occasions from tract } g \text{ in month } t}.$$

The outside option absorbs all remaining occasions: eating at home, visiting establishments outside our POI universe, or not dining at all.

We present results under two market-share definitions that bracket the likely range of true shares.

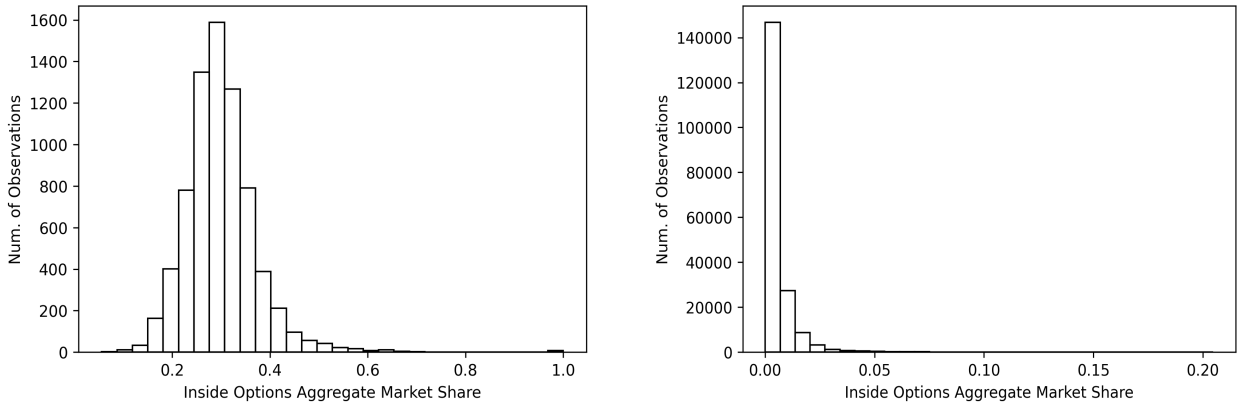
Conservative definition. Unobserved visits are treated as outside-option choices. A restaurant with no visits from a given tract in a given month receives a zero inside-option share for that cell. This definition likely overstates true shares, however, because consumers who dine at home without carrying or activating their device are excluded from the denominator, shrinking the count of potential dining occasions and mechanically inflating nonzero shares. The resulting distribution, shown in Figure 1a, is centered around 0.25–0.35, somewhat above national benchmarks of 18–19 percent for away-from-home dining (NHANES and ATUS estimates).

Imputed definition. In cellphone-based origin-destination flow data, zeros often arise because the observed sample represents only a fraction of the true population, and many potential census tract (CT)-POI-month combinations exhibit zero counts due to sampling error and behavioral sparsity. Common fixes such as dropping zeros, aggregating markets, or adding small constants alter the effective choice set and can bias elasticity and welfare estimates. Building on J. Li (2019) and Cheng and Wan (2025), we adapt the empirical Bayes (EB) correction to the context of restaurant demand, transforming observed visitation shares into posterior mean estimates that remain strictly positive and theoretically consistent while preserving the full choice set.

Specifically, we construct a prior distribution for each CT-POI-month pair using visitation data from a set of nearby restaurants. For each focal CT-POI-month observation, we pool information from the 50 most comparable CTs, where comparability is defined by having similar travel distance to the same restaurant. The choice of 50 balances two goals: (i) borrowing enough observations to estimate a stable Beta prior, and (ii) keeping the pooled markets geographically and behaviorally close so that implicit travel costs are comparable. Travel distance here serves as a proxy for the "price" of visiting a restaurant, so restricting to CBGs with similar distances ensures that the prior reflects similar effective costs. We then model visit probabilities using a Beta-Binomial distribution, which shrinks observed zeros toward expected visitation rates in these comparable markets while avoiding oversmoothing. This correction stabilizes the estimates and better reflects true restaurant demand. Meanwhile, this is theoretically consistent with the random-coefficient logit framework and preserves the full choice set.

By filling in zero-visit cells with small but positive predicted shares, imputation pulls the distribution toward smaller values, as seen in Figure 1b. The two definitions thus reflect two opposing biases—denominator undercounting inflating the conservative shares, and numerator-side attrition driving many cells to zero in the non-imputed case—and together bracket the plausible range of true market shares. We treat the imputed definition as a lower bound and report it in Appendix A alongside the main results.

Figure 1: Distribution of inside-option market shares under the two definitions



(a) Conservative definition

(b) Imputed definition

Note: The conservative definition yields a bell-shaped distribution centered around 0.20–0.35, reflecting denominator undercounting from devices inactive at home. The imputed definition fills zero-visit cells via a Bayesian procedure (Cheng & Wan, 2025; J. Li, 2019), producing smaller shares concentrated near zero. Together they bracket the plausible range of true market shares.

3.3 EV Charging Station Access and Restaurant Visits

Charging station locations and open dates are drawn from the U.S. Department of Energy Alternative Fuels Station Locator. We retain all the charging stations that were open to the public as of each month in 2019. For each restaurant-month observation, the treatment variable is:

$$EVCS_{jmt} = \mathbf{1}\{\text{at least one public charger within 500m of restaurant } j \text{ in month } t\}.$$

Approximately 38 percent of restaurant-month observations have a charging station within 500 meters. Stations are concentrated in the dense commercial corridors of downtown Kansas City and along major arterials, with sparser coverage in suburban and rural areas on both the Missouri and Kansas sides of the metro boundary.

Figure 2a shows the spatial distribution of public charging stations across the Kansas City DMA in 2019. Stations are heavily concentrated in the downtown core and along major commercial arterials, with sparse coverage in the suburban and rural periphery on both sides of the state border. Figure 2b overlays the restaurant locations, illustrating the degree of spatial overlap between charging infrastructure and the dining establishments in our sample.

Each purple dot represents a restaurant POI; each blue dot a public charging station. The clustering of both layers in the urban core is evident, motivating our controls for road and population density.

Figure 2: Spatial distribution of EV charging stations and restaurant POIs



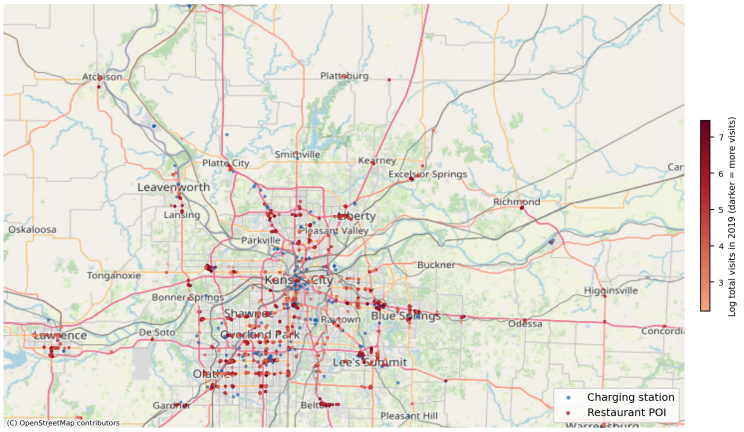
(a) Charging stations

(b) Charging stations and restaurant POIs

Note: Blue dots are public charging stations in the Kansas City DMA in 2019; purple dots are restaurant POIs in our sample.

Figure 3 maps restaurant visitation intensity alongside charging stations. Each red dot is a restaurant POI, with color darkness scaled to log total visits in 2019; darker red indicates more visits. The overlap between high-visit restaurants and charging station locations provides visual motivation for the positive reduced-form correlation we exploit, while the substantial variation in visit intensity among restaurants equidistant from chargers underscores the need for the structural demand framework developed in Section 4.

Figure 3: Restaurant visit intensity and charging station locations



Note: Red dots are restaurant POIs in Kansas City DMA in 2019; color darkness reflects log total visits (darker = more visits). Blue dots are public charging stations.

3.4 Travel Costs and Control Variables

Travel cost c_{jmt} is imputed from the straight-line distance between the centroid of tract g and restaurant j, converted to a monetary cost using two components: (i) the average gasoline price in month t, multiplied by the implied fuel consumption for the implied round-trip distance, and (ii) the value of travel time, computed as the median hourly wage implied by the median household income of tract g, multiplied by estimated travel duration. This measure varies across tracts (income heterogeneity), across restaurants (distance heterogeneity), and over time (fuel-price variation).

Restaurant characteristics X_{jmt} include: log road density within 500m and 2,000m buffers; log population density within 500m and 2,000m buffers; log population of the restaurant's census block; log population of the restaurant's census tract; and the interaction of log median household income at the restaurant's census block level with an urban-group indicator that classifies each restaurant as being in core Kansas City, other Missouri, or other Kansas. The latter interactions capture heterogeneous income gradients of demand across the urban-rural spectrum.

Fixed effects absorb: census-tract preferences (λ_g), restaurant-brand quality ($\mu_{b(j)}$), county-level location amenities ($\eta_{\ell(j)}$), and aggregate monthly demand shocks (ζ_t).

Table 1 presents summary statistics for the main variables.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Median	Max
Panel A: Restaurant–Market Observations					
Inside-option share (s_{jmt})	0.009	0.012	0.000	0.005	0.500
EVCS within 500m (0/1)	0.381	0.486	0	0	1
Travel cost ($)	11.49	13.68	0.02	7.01	185.28
Scaled travel cost	0.840	1.000	0.001	0.512	13.547
Panel B: Restaurant Characteristics					
Road density, 500m buffer (km/km^2)	12.48	4.89	4.18	11.35	35.01
Population density, 500m buffer (000s/km^2)	0.89	0.53	0.01	0.82	2.87
Block-level population (000s)	1.88	0.95	0.44	1.63	4.99
Tract median income ($000s)	67.1	28.5	17.2	63.6	182.6
Panel C: Market Composition					
Restaurants per market ($\lvert\mathcal{J}_m\rvert$)	26.4	17.2	1	23	122
Inside-option share, market total	0.227	0.075	0.005	0.230	0.667
Fraction of markets with ≥1 EVCS POI	0.972	–	–	–	–
Panel D: Instrument Characteristics					
Simulated ports within 500m (road-density grid)	1.78	4.53	0	0	48
Simulated ports within 1000m (road-density grid)	7.14	11.17	0	1	88
Future peripheral ports, 2–4km annulus	20.20	22.19	0	16	199

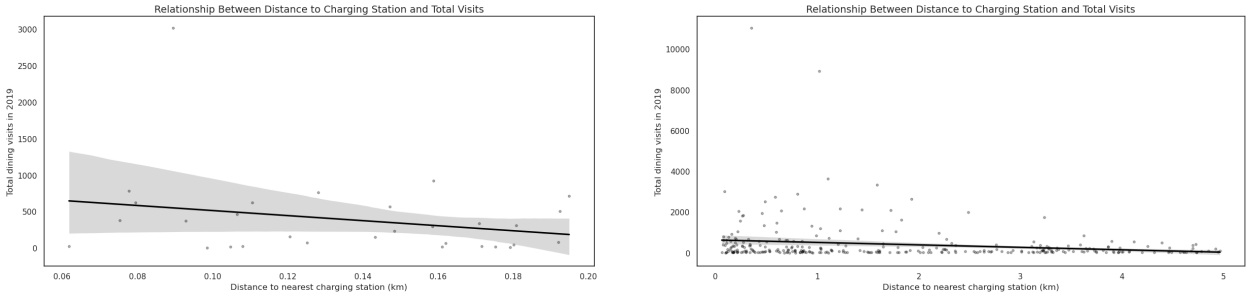
Note: Panel A is at the restaurant–tract–month level. Travel cost is in dollars (unscaled). Scaled travel cost is divided by the sample standard deviation $\sigma_C = 13.68$. Instruments in Panel D are aggregated to the restaurant–month level and interacted with urban-group indicators in estimation.

3.5 Reduced-Form Evidence on Charging Proximity

Before turning to the structural model, Figures 4a and 4b provide simple visual evidence of the relationship between charging proximity and restaurant visits. Each point is a restaurant POI. The x-axis measures the distance (in km) to the nearest public charging station; the y-axis measures total dining visits from Kansas City residents in 2019, defined as device-visits between 6–10 pm with a dwell of at least 30 minutes. The solid line is a linear fit with 95 percent confidence band.

Figure 4a restricts to restaurants within 200 meters of a charging station—effectively walking distance—and shows a clear negative relationship: restaurants located closer to a charger receive more visits. Figure 4b extends the window to 5 km, and the negative gradient remains visible, though noisier as distance increases and the amenity effect attenuates. Together, the two panels suggest that the benefit of nearby charging decays with distance, consistent with a localized amenity mechanism rather than a broad area-level effect. These patterns are unconditional and do not account for the endogenous placement of charging stations; the structural model in Section 4 addresses this directly.

Figure 4: Total dining visits versus distance to nearest charging station



(a) Samples within 200m of a charging station

(b) Samples within 5km of a charging station

Note: Each point is a restaurant POI. Visits are defined as device-visits between 6–10 pm with a dwell of at least 30 minutes, from residents of the Kansas City DMA in 2019. The line is an OLS fit with 95% confidence band.

4 Demand Model

We specify a model of restaurant choice to estimate the demand effects and welfare implications of proximity to EV charging infrastructure. We use a discrete-choice framework following S. Berry et al. (1995). In each period, consumers choose whether to visit one of the restaurants in their choice set or select an outside option that includes dining at home, visiting unobserved establishments, or engaging in other non-dining activities.

The choice set consists of restaurants located within a feasible travel distance from the consumer's home census tract, reflecting the geographic scope of typical dining trips. A market is defined as a CT-by-month combination, so that consumers within the same CT and period face a common set of alternatives but differ in their travel costs to each location.

Under this definition, market shares are defined over restaurants and the outside option and sum to one within each CT–month market.

We assume that demand is static: consumers make myopic choices in each period and do not account for future changes in charging infrastructure, travel costs, or restaurant characteristics. This assumption is appropriate in our setting given the short decision horizon of dining choices and allows us to estimate a tractable model of substitution across nearby establishments.

4.1 Utility and Mean Utility

Consumer i's indirect utility from visiting restaurant j in market $m = (t, g)$ is:

$$u_{ijmt} = \delta_{jmt} + \mu_{ijmt} + \varepsilon_{ijmt}, \tag{1}$$

where $\varepsilon_{ijmt} \overset{\text{iid}}{\sim}$ Type-I Extreme Value. Utility consists of three parts: a mean utility component δ_{jmt} that is common across consumers in market m, an individual-specific deviation μ_{ijmt} that captures heterogeneous tastes, and an idiosyncratic shock ε_{ijmt}. Mean utility is:

$$\delta_{jmt} = \beta^{EVCS} EVCS_{jmt} + \beta^{c}\tilde{c}_{jmt} + X'_{jmt}\beta + \lambda_g + \mu_{b(j)} + \eta_{\ell(j)} + \zeta_t + \xi_{jmt}, \tag{2}$$

where $\tilde{c}_{jmt} = c_{jmt}/\sigma_C$ is the scaled travel cost and ξ_{jmt} is an unobserved demand shock capturing restaurant quality or appeal that varies at the market level.

The coefficient β^{EVCS} measures the average demand effect of having at least one public charging station within 500 meters of restaurant j in month t. In our setting, this coefficient should be interpreted broadly: because we do not observe individual vehicle ownership, $EVCS_{jmt}$ captures the aggregate amenity value of charging access, including potential complementarities for EV drivers, as well as broader signaling or neighborhood-improvement effects that may affect all consumers. The coefficient β^c captures the average disutility of travel cost, so more distant or time-consuming trips reduce utility. The vector X_{jmt} includes observed restaurant and neighborhood characteristics that may also affect demand.

Consumer heterogeneity enters through:

$$\mu_{ijmt} = \sigma^c \nu_i \tilde{c}_{jmt}, \qquad \nu_i \overset{\text{iid}}{\sim} N(0,1). \tag{3}$$

When $\sigma^c = 0$, the model reduces to the standard (homogeneous) logit. A positive σ^c generates flexible substitution patterns that depend on travel-cost similarity across alternatives, relaxing the independence-of-irrelevant-alternatives (IIA) problem. This heterogeneity is important in our setting because charging infrastructure may matter more for consumers who are already willing to make longer trips or to substitute across a wider geographic choice set.

4.2 Predicted Shares and Inversion

Aggregating over the distribution of ν_i, the predicted market share of restaurant j in market m is:

$$\hat{s}_{jmt}(\delta_{mt}, \sigma^c) = \int \frac{\exp(\delta_{jmt} + \sigma^c \nu \tilde{c}_{jmt})}{1 + \sum_{k \in \mathcal{J}_m} \exp(\delta_{kmt} + \sigma^c \nu \tilde{c}_{kmt})} \phi(\nu)\, d\nu, \tag{4}$$

where $\phi(\cdot)$ is the standard normal density and the denominator includes the outside option (normalized to zero utility). The outside option captures all alternatives to visiting one of the restaurants in our point-of-interest universe, including eating at home, visiting establishments outside the observed sample, or not dining out during the relevant time window.

Given any value of σ^c, S. T. Berry (1994) shows that, under mild regularity conditions, the mapping from mean utilities to market shares is invertible market by market. Thus, for each candidate value of σ^c, there exists a unique vector $\hat{\delta}_{mt}(\sigma^c)$ that exactly rationalizes the observed market shares s_{mt}. This inversion is central to estimation because it allows us to recover the unobserved mean utility levels implied by the data and then relate them to observed characteristics, charging access, and travel cost.

4.3 Willingness-to-Pay

Given estimates $(\hat{\beta}^{EVCS}, \hat{\beta}^c)$, the willingness-to-pay for a discrete change $EVCS : 0 \to 1$, expressed in dollars, is:

$$WTP^{\$} = -\frac{\hat{\beta}^{EVCS}}{\hat{\beta}^c/\sigma_C} = -\frac{\hat{\beta}^{EVCS}\,\sigma_C}{\hat{\beta}^c}. \tag{5}$$

In the random-coefficients model, travel-cost sensitivity is consumer-specific, so WTP is also heterogeneous:

$$WTP_i^{\$} = -\frac{\hat{\beta}^{EVCS}\,\sigma_C}{\hat{\beta}^c + \hat{\sigma}^c\,\nu_i}. \tag{6}$$

We summarize this distribution using quadrature draws and report the mean. We also express WTP relative to the average trip cost:

$$WTP^{\%} = 100 \times \mathbb{E}_i\left[\frac{WTP_i^{\$}}{c_i}\right], \tag{7}$$

which provides an interpretable, unit-free metric of the charging amenity value relative to what consumers already spend to reach a restaurant. In our context, this scaling is particularly useful because travel costs vary substantially across census tracts and restaurants, so a dollar-valued willingness-to-pay estimate alone can be difficult to interpret across markets.

5 Identification and Estimation

Our goal is to identify the causal effect of charging proximity and travel cost on restaurant demand. The key empirical challenge is that both charging availability and travel cost are endogenous to unobserved demand shocks. We address these concerns using multiple sources of exogenous variation that exploit predetermined geographic features, future infrastructure deployment, and global energy-market shocks.

5.1 Endogeneity Concerns

Consistent estimation of β^{EVCS} and β^c requires that the instruments be uncorrelated with ξ_{jmt}. Two violations of this condition are likely.

Supply-side endogeneity of EVCS. Charging operators have strong commercial incentives to deploy infrastructure near high-traffic, high-quality establishments. Restaurants with high latent demand ($\xi_{jmt} > 0$) are precisely those that attract station deployment, creating a positive correlation between $EVCS_{jmt}$ and ξ_{jmt}. OLS would therefore overstate the causal effect of charging on visits—yet in our data, the OLS estimates are substantially smaller than the IV estimates, suggesting that other downward biases (measurement error, attenuation from device-panel incompleteness) more than offset the supply-side upward bias.

Demand-side endogeneity of travel cost. Bradt (2025) documents that consumers who have strong preferences for particular restaurants systematically choose to locate closer to them, inducing negative correlation between observed travel distance and ξ_{jmt}. This causes the OLS coefficient on travel cost to be biased toward zero (in absolute value), in turn inflating the implied WTP from OLS. Instrumenting for travel cost is therefore essential for obtaining credible welfare estimates.

5.2 Instrument Families

We construct three complementary families of instruments that exploit different sources of exogenous variation. Each instrument is designed to affect either charging availability or travel cost while remaining orthogonal to contemporaneous demand shocks.

Simulated charging exposure from predetermined geography. We construct instruments using counts and distances to simulated charging station locations generated from predetermined spatial features—road-density and population-density grids—via a k-means clustering algorithm. For each restaurant, we compute: (a) the number of simulated ports within 500m; (b) the number within 1,000m; and (c) the log distance to the nearest simulated station. Controlling directly for the underlying geographic features in the regression, this simulated exposure is designed to be orthogonal to contemporaneous ξ_{jmt} while remaining predictive of actual charging availability. The logic is analogous to the hypothetical-network instrument of Faber (2014): geographic suitability for charging deployment predicts realized deployment without responding to local demand conditions, condtional on the control variables.

Future peripheral deployment. We aggregate charging ports that open at least six months after month t within a 2–4 km peripheral annulus around each restaurant. Because these openings lie in the future relative to when demand is measured, they isolate persistent spatial patterns of charging investment without contamination by contemporaneous supply-demand correlation. This instrument provides an independent source of variation from the simulated-network instrument and tends to produce somewhat larger EVCS estimates (see Table 9).

Oil-market shifters for travel cost. We use oil-supply and oil-demand shocks from the structural decomposition of Bradt (2025), interacted with the predetermined distance from each tract centroid to each restaurant (a shift-share design). Oil-market conditions move per-unit travel costs, with larger effects for longer trips. Because these shocks originate in

global commodity markets, they are plausibly orthogonal to local restaurant quality shocks ξ_{jmt}.

All three instrument families are interacted with indicators for the three urban-group categories to allow heterogeneous first-stage relationships across the urban-rural gradient. First-stage partial F-statistics across all specifications higher than 200, well above conventional strong-instrument thresholds.

5.3 GMM Estimation

For a given value of σ^c, the Berry inversion yields implied mean utilities $\hat{\delta}_{jmt}(\sigma^c)$. We treat $\xi_{jmt} = \hat{\delta}_{jmt} - (\beta^{EVCS}\, EVCS_{jmt} + \beta^c\, \tilde{c}_{jmt} + X'_{jmt}\beta + \text{FE})$ as the structural error and form the GMM moment conditions:

$$\mathbb{E}[Z'_{jmt}\, \xi_{jmt}] = 0, \tag{8}$$

where Z_{jmt} collects all excluded instruments alongside the exogenous controls. The outer loop searches over σ^c to minimize the GMM objective; the inner loop solves for $(\beta^{EVCS}, \beta^c, \beta)$ by two-stage least squares. Standard errors are clustered at the census-tract (population-group) level to account for within-neighborhood correlation across restaurants visited by consumers from the same tract. We implement the estimation using PyBLP (Conlon & Gortmaker, 2020).

6 Estimation Results

6.1 Main Results

Table 2 reports estimates under the conservative market-share definition. Column (1) is OLS under the standard logit; columns (2)–(4) are IV estimates under the standard logit using three instrument variants; and columns (5)–(7) are IV estimates under the random-coefficients logit using the same three variants.

Effect of charging infrastructure. The OLS coefficient on $EVCS_{jmt}$ is 0.046, but instrumenting amplifies this substantially. Across the logit IV columns (2)–(4), the coefficient ranges from 0.230 to 0.279; across the RC logit IV columns (5)–(7), it ranges from 0.174 to 0.253—all statistically significant. The large gap between OLS and IV suggests that downward biases from measurement error and thin markets dominate the upward supply-side confound, so naive OLS substantially understates the true effect.

Travel cost and random coefficient. The OLS travel-cost coefficient is modest at -0.318. IV raises this to -0.566 in column (5) and -0.668 in column (6), consistent with Bradt (2025): consumers who favor a restaurant tend to live nearby, so OLS underestimates the true disutility of distance. The estimated standard deviation of the random coefficient $\hat{\sigma}^c$ ranges from 0.353 to 0.433 across columns (5)–(7), precisely estimated in all three. This dispersion matters: consumers with low travel-cost sensitivity have WTP well above the mean, while high-sensitivity consumers have WTP well below—a pattern that the standard logit

cannot capture. This heterogeneity implies that the benefits of charging infrastructure are uneven across consumers, with larger gains concentrated among those with lower travel-cost sensitivity.

Willingness-to-pay. OLS yields $WTP^{\%} \approx 58$ percent of average trip cost. Column (5) gives $WTP^{\%} = 180$ percent, substantially higher. The RC logit produces more moderate WTP than the plain logit because the IV correction to the travel-cost coefficient is larger in the RC model. To put column (5) in concrete terms: given the sample-mean travel cost of \$11.49, the 180 percent WTP implies the average consumer would pay roughly \$20.68 more to dine at a restaurant with nearby charging infrastructure rather than a comparable alternative—a substantial premium that reflects the aggregate amenity value of charging access across all diners, regardless of vehicle ownership. Importantly, this WTP reflects not only direct benefits to EV users, but also broader improvements in trip reliability and flexibility, which affect overall destination choice.

Control variables. Road density within 500m is positive and significant throughout, consistent with better access generating more foot traffic. Population density within 500m is negative conditional on controls, suggesting density intensifies within-market competition more than it expands the total dining pool. Block- and tract-level population are positive and significant in IV columns, consistent with larger local pools generating more visits. The income interactions are large and highly significant: the income elasticity of restaurant demand is markedly higher in rural Missouri (≈ 0.93) than in rural Kansas (≈ 0.15) or urban areas (≈ 0.22), pointing to systematic differences in the income–consumption relationship across the metro gradient. This suggests that the demand response to infrastructure may vary substantially across regions, with stronger effects in higher-elasticity areas.

6.2 Market Share Definition: Conservative vs. Imputed

Table 4 in Appendix A replicates the analysis using imputed market shares. The EVCS coefficient in the RC logit 500m IV column rises to 0.520 from 0.253 in the main table, and the travel-cost coefficient nearly quadruples in absolute value. This pattern reflects a systematic difference in how the two share constructions treat sparse markets. The conservative definition treats zero-visit cells as true outside-option choices, which attenuates estimated demand sensitivity. In contrast, the imputed shares partially recover latent demand in these cells, leading to larger estimated responses to both charging access and travel cost.

Interestingly, the WTP percentage falls to 87.5 percent because the travel-cost denominator grows disproportionately fast. This highlights that willingness-to-pay is jointly determined by both the numerator (charging effect) and the denominator (travel-cost sensitivity), and that correcting attenuation in travel cost can mechanically reduce implied WTP even when the charging coefficient increases. Rather than interpreting the imputed specification as an upper bound, we view the two approaches as bracketing the true demand system: the conservative shares likely understate substitution patterns due to measurement error, while the imputed shares may overstate them by smoothing across markets.

Table 2: BLP Demand Estimates: Main Results (Conservative Market Shares, Cuebiq-Tracked Visits)

	Logit (OLS)	Logit (IV)			RC Logit (IV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument Var.	–	500m	1000m	log(dist)	500m	1000m	log(dist)
EVCS within 500m	0.046***	0.279***	0.233***	0.230***	0.253***	0.174***	0.185***
	(0.012)	(0.051)	(0.049)	(0.041)	(0.046)	(0.045)	(0.038)
Travel cost (scaled)	−0.318***	−0.320***	−0.320***	−0.319***	−0.566***	−0.668***	−0.630***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.092)	(0.101)	(0.096)
$\sigma_{\text{travel cost}}$					0.353***	0.433***	0.405***
					(0.074)	(0.074)	(0.073)
log(RoadDens$_{500m}$)	0.042***	0.054***	0.053***	0.052***	0.047***	0.041***	0.042***
	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)
log(RoadDens$_{2000m}$)	−0.040	−0.040	−0.043	−0.038	−0.018	−0.010	−0.010
	(0.044)	(0.043)	(0.043)	(0.043)	(0.039)	(0.039)	(0.039)
log(PopDens$_{500m}$)	−0.001	−0.049***	−0.040**	−0.039**	−0.042***	−0.025	−0.027*
	(0.014)	(0.017)	(0.017)	(0.016)	(0.015)	(0.016)	(0.014)
log(PopDens$_{2000m}$)	−0.028	0.017	0.009	0.007	0.006	−0.013	−0.010
	(0.033)	(0.032)	(0.035)	(0.032)	(0.029)	(0.031)	(0.028)
log(POI Pop)	0.047***	0.068***	0.064***	0.064***	0.059***	0.050***	0.051***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)
log(POI Pop (Tract))	−0.001	0.055***	0.044***	0.043***	0.046***	0.025*	0.029**
	(0.012)	(0.016)	(0.016)	(0.014)	(0.014)	(0.015)	(0.013)
log(POI income) × Rural KS	0.103	0.103	0.092	0.101	0.145*	0.156*	0.156*
	(0.082)	(0.081)	(0.075)	(0.081)	(0.083)	(0.080)	(0.084)
log(POI income) × Rural MO	0.732***	0.936***	0.882***	0.890***	0.921***	0.814***	0.836***
	(0.115)	(0.111)	(0.123)	(0.121)	(0.111)	(0.124)	(0.121)
log(POI income) × Urban	0.187***	0.182***	0.183***	0.183***	0.221***	0.237***	0.232***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.017)	(0.017)	(0.017)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	57.96%	350.00%	293.21%	289.05%	179.79%	104.42%	117.91%

[a] Standard errors (clustered at census tract) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[b] Fixed effects: visitor census tract + month + POI brand + POI county.

[c] Travel cost is standardized by its sample standard deviation $\sigma_C = 13.677$. "Mean WTP (% of travel cost)" is $100 \times \mathbb{E}[WTP_i^{\$}/c_i]$ for a $0 \to 1$ change in EVCS-within-500m.

[d] Columns (1)–(4) are standard logit; columns (5)–(7) allow a random coefficient on scaled travel cost. $\hat{\sigma}^c$ reports the estimated standard deviation of that coefficient.

[e] IV specifications instrument EVCS-within-500m using simulated peripheral port exposure (counts within 500m or 1,000m, or log distance to nearest simulated station), interacted with urban-group category.

6.3 Robustness Checks

Appendix B presents a battery of robustness checks, all of which tell a consistent story.

Alternative instrument families. Table 9 pairs three spatial instruments with two oil-shock shifters across six logit IV specifications. The EVCS coefficient is stable across all columns, ranging from roughly 0.185 to 0.378. The future-peripheral-openings instrument tends to produce the largest estimates, while the population-density simulated instrument produces the smallest; neither is an outlier. Tables 10 and 11 show the same pattern holds for the 1,000m and log-distance instrument families.

This stability across instrument constructions is important because each instrument relies on different identifying variation—predetermined geography, future infrastructure placement, and global energy shocks. The consistency of the estimates suggests that the results are not driven by a particular exclusion restriction, but instead reflect a common underlying demand response to charging availability.

Alternative market-share definition. To address concerns that the baseline share definition may overweight frequent visitors, we construct an alternative measure based on unique agents by month, which counts each device at most once per location within a period. Table 5 uses a share definition based on unique agents by month and yields an EVCS coefficient of 0.219 in the RC logit 500m IV column—close enough to the main estimate to confirm that the findings are not an artifact of how device-occasion counts are constructed.

This alternative measure shifts the focus from the intensive margin (how often individuals visit) to the extensive margin (whether they visit at all), thereby reducing the influence of high-frequency users who may otherwise disproportionately drive aggregate visit counts. The similarity of the estimates across the two definitions indicates that the charging effect operates primarily through location choice rather than repeated visitation, and is not driven by a small subset of heavy users.

Sample restrictions. To address concerns that sparse mobility data in low-volume tracts may introduce measurement error and distort estimated demand responses, we drop tracts with fewer than 100 or 500 annual visits. The estimates (in Tables 6 and 7) remain essentially unchanged, ruling out the possibility that thin markets with noisy shares are driving the results.

Market share rescaling. Complementing this exercise, we assess the sensitivity of the results to assumptions about market size and the outside option by rescaling market shares. Halving all market shares to stress-test the outside-option level (Table 8) also produces estimates nearly identical to the baseline.

7 Counterfactual Analysis

7.1 Counterfactual Framework

Let $p_i \equiv EVCS_{jmt}$ denote the observed charging indicator and δ_i^{cur} the estimated mean utility. We define two global counterfactual mean-utility vectors:

$$\delta_i^{all0} = \delta_i^{cur} - \hat{\beta}^{EVCS} p_i, \tag{9}$$

$$\delta_i^{all1} = \delta_i^{cur} + \hat{\beta}^{EVCS}(1 - p_i). \tag{10}$$

Counterfactual shares $s_i(\delta)$ are computed via the Berry inversion, integrating over consumer heterogeneity using the estimated $\hat{\sigma}^c$. The percent change in restaurant i's visit share from scenario A to scenario B is:

$$\Delta_i^{A \to B} = \frac{s_i(\delta^B) - s_i(\delta^A)}{s_i(\delta^A)}, \tag{11}$$

where the outside-option share under scenario A is $s_{0m}(\delta^A) = 1 - \sum_{i \in \mathcal{J}_m} s_i(\delta^A)$. All results below are based on the 500m simulated-port IV specifications—columns (2) and (5) of Table 2 for the Logit IV and RC IV cases respectively—and their imputed-share counterparts. The full set is summarized in Table 3. We focus the discussion on the RC IV column (5) estimates, which allow for consumer heterogeneity in travel-cost sensitivity and generate more flexible substitution patterns.

7.2 Business Stealing

The central question of this section is how much of a restaurant's visit gain from a nearby charger represents genuinely new activity versus visits poached from competitors. We answer it by comparing two experiments. In the first, every restaurant without a charger gains one simultaneously. In the second, a single restaurant gains a charger while all others stay the same.

Under universal deployment, upgraded restaurants see their visit shares rise by 20.56 percent on average. Under the single-restaurant experiment, the treated establishment gains 28.53 percent. The gap exists because in the marginal case the restaurant captures a competitive advantage over its neighbors; when everyone upgrades simultaneously, that advantage is eroded. The implied business-stealing share is:

$$\text{Business-stealing share} = \frac{28.53 - 20.56}{28.53} \approx 27.9\%. \tag{12}$$

This result is stable across both IV specifications and both share definitions in Table 3, ranging from 23 to 30 percent. The policy implication is direct: a restaurant perceives a 28.5 percent visit gain from a nearby charger, but roughly 7.9 percentage points of that are simply transfers from neighboring establishments. Optimal subsidies for charging infrastructure, if implemented, should be discounted by roughly 28 percent relative to what private valuations would suggest.

7.3 Aggregate Industry Effects

Realized impact of the existing network. Relative to a counterfactual with no charging stations, the existing network has already raised average restaurant visit shares by 8.5 percent and reduced the market-level outside share by 1.9 percent. Charging infrastructure is already meaningfully reshaping where people dine across Kansas City.

Potential gain from universal deployment. Extending charging to all restaurants from the current baseline would add a further 12.8 percent to average visit shares and reduce the outside share by 3.78 percent. Roughly 30 percent of this gain would represent genuinely new dining occasions; the rest is reallocation among existing restaurants.

Together, these two exercises imply that universal deployment would achieve about 1.5 times the impact already delivered by the existing network—a diminishing-returns pattern consistent with today's chargers being disproportionately located near the highest-demand restaurants. The marginal establishments to be electrified are in lower-traffic areas and would generate smaller per-establishment effects.

Table 3 summarizes all results. The Logit IV and RC IV columns tell a consistent story, and the imputed-share estimates—while larger in level—preserve the same qualitative patterns throughout.

Table 3: Counterfactual Summary

	Conservative		Imputed	
	Logit IV	RC IV	Logit IV	RC IV
Business stealing:				
Global policy (% visit change)	23.26%	20.56%	67.06%	47.34%
Marginal investment (% visit change)	31.81%	28.53%	87.23%	67.40%
Business-stealing share	26.9%	27.9%	23.1%	29.7%
Realized impact of existing network:				
Avg. % visit gain	9.64%	8.48%	29.18%	20.79%
Outside option Δ	−2.11%	−1.91%	−2.46%	−2.03%
Potential gain from universal deployment:				
Avg. % visit gain	14.44%	12.77%	41.38%	29.56%
Outside option Δ	−4.28%	−3.78%	−6.85%	−5.06%

Note: All IV specifications use the 500m simulated-port instrument paired with oil-market shifters; see Section 5. Logit IV and RC IV correspond to columns (2) and (5) of Table 2, respectively, and their imputed-share counterparts in Table 4. Conservative shares treat unobserved visits as outside-option choices; imputed shares use Bayesian filling (Cheng & Wan, 2025; J. Li, 2019). Business-stealing share = (marginal − global) / marginal.

8 Conclusion

This paper estimates how public EV charging infrastructure shapes restaurant visit behavior, consumer welfare, and competitive dynamics in Kansas City in 2019. Three findings stand

out. First, proximity to a charging station has a large causal effect on restaurant visits, raising visit share by 20–28 percent. Second, consumers are willing to incur roughly 180 percent of their average trip cost to dine at a restaurant with nearby charging infrastructure rather than a comparable alternative—capturing the aggregate amenity value of this infrastructure across all visitors, not solely EV owners. Third, roughly one-quarter to one-third of any individual restaurant's gain represents business stealing from competitors rather than net new activity—implying that the private return to hosting a charger meaningfully exceeds the social return.

Our counterfactual analysis shows that the existing network has already raised industry-wide visits by 8–9 percent, and universal deployment would add a further 13 percent. These results highlight that EV charging infrastructure not only affects individual location choices but also reshapes market-level demand and competitive allocation across firms. Together, these estimates provide a concrete empirical foundation for designing infrastructure policies.

The analysis is confined to a single metro area in a single year when EV penetration was still modest, and the estimated effects may evolve as ownership becomes more widespread. In particular, as EV adoption increases, both the magnitude and the distribution of these effects may change, potentially amplifying network externalities and competitive spillovers. Future work incorporating multiple markets, tract-level EV ownership data would substantially enrich these findings.

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Appendix A Main Results: Imputed Market Shares

Table 4 replicates Table 2 using the Bayesian-imputed market-share definition. The EVCS coefficient in the RC logit 500m IV specification is 0.520 (vs. 0.253 in the main table). The WTP percentage falls to 87.5 percent because the travel-cost coefficient grows proportionally more. All other qualitative patterns are preserved.

Appendix B Robustness Tables

B.1 Alternative Market Share Definition

B.2 Subsample: Drop Census Tracts with Fewer than 100 Annual Visits

B.3 Subsample: Drop Census Tracts with Fewer than 500 Annual Visits

B.4 Market Share Halved (Outside Option Sensitivity)

Appendix C Instrument Robustness: Logit Model

Appendix D Reduced-Form Results

Tables 12 and 13 present OLS and IV second-stage estimates and the corresponding first-stage results, respectively, for a reduced-form specification that regresses restaurant visits directly on the charging indicator and controls with county fixed effects. These regressions impose no model structure and provide a model-free benchmark confirming the positive reduced-form relationship between charging proximity and restaurant visits.

Table 4: BLP Demand Estimates: Imputed Market Shares

	Logit (OLS)	Logit (IV)			RC Logit (IV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument Var.	–	500m	1000m	log(dist)	500m	1000m	log(dist)
EVCS within 500m	0.096***	0.630***	0.587***	0.528***	0.520***	0.378***	0.307***
	(0.015)	(0.078)	(0.077)	(0.060)	(0.057)	(0.076)	(0.051)
Travel cost (scaled)	−0.712***	−0.726***	−0.724***	−0.724***	−2.390***	−2.991***	−3.816***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.357)	(0.551)	(0.491)
$\sigma_{\text{travel cost}}$					1.102***	1.385***	1.760***
					(0.168)	(0.254)	(0.222)
log(RoadDens$_{500m}$)	0.063***	0.094***	0.091***	0.087***	0.055***	0.034	0.022
	(0.021)	(0.024)	(0.024)	(0.023)	(0.020)	(0.022)	(0.021)
log(RoadDens$_{2000m}$)	−0.173***	−0.154**	−0.154**	−0.156**	−0.017	0.022	0.070
	(0.065)	(0.064)	(0.064)	(0.064)	(0.051)	(0.059)	(0.054)
log(PopDens$_{500m}$)	−0.007	−0.124***	−0.117***	−0.104***	−0.097***	−0.072***	−0.060***
	(0.018)	(0.024)	(0.024)	(0.022)	(0.017)	(0.019)	(0.017)
log(PopDens$_{2000m}$)	−0.061	0.055	0.049	0.036	−0.005	−0.040	−0.060*
	(0.050)	(0.052)	(0.054)	(0.052)	(0.036)	(0.038)	(0.034)
log(POI Pop)	0.067***	0.117***	0.114***	0.107***	0.088***	0.075***	0.069***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.012)	(0.014)	(0.014)
log(POI Pop (Tract))	0.023	0.145***	0.135***	0.121***	0.093***	0.050*	0.019
	(0.019)	(0.026)	(0.026)	(0.023)	(0.020)	(0.029)	(0.022)
log(POI income) × Rural KS	0.387***	0.383***	0.383***	0.387***	0.626***	0.702***	0.777***
	(0.076)	(0.074)	(0.073)	(0.073)	(0.083)	(0.101)	(0.086)
log(POI income) × Rural MO	1.447***	1.960***	1.925***	1.885***	1.941***	1.881***	1.905***
	(0.123)	(0.139)	(0.141)	(0.133)	(0.143)	(0.168)	(0.196)
log(POI income) × Urban	0.391***	0.382***	0.380***	0.383***	0.588***	0.639***	0.706***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.039)	(0.051)	(0.042)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	54.09%	348.63%	326.11%	293.09%	87.48%	50.74%	32.33%

[a] Standard errors (clustered at census tract) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[b] Market shares use Bayesian imputation following J. Li (2019) and Cheng and Wan (2025); see Section 3.
[c] Columns (1)–(4) are standard logit; columns (5)–(7) allow a random coefficient on scaled travel cost. $\hat{\sigma}^c$ reports the estimated standard deviation of that coefficient.
[d] All other notes identical to Table 2.

Table 5: BLP Demand Estimates: Alternative Market Share Definition, Unique Agents by Month)

	Logit (OLS)	Logit (IV)			RC Logit (IV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument Var.	–	500m	1000m	log(dist)	500m	1000m	log(dist)
EVCS within 500m	0.048***	0.279***	0.219***	0.226***	0.219***	0.080*	0.140***
	(0.012)	(0.049)	(0.048)	(0.041)	(0.040)	(0.045)	(0.036)
Travel cost (scaled)	−0.315***	−0.316***	−0.316***	−0.316***	−0.848***	−1.150***	−0.865***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.100)	(0.143)	(0.105)
$\sigma_{\text{travel cost}}$					0.477***	0.620***	0.486***
					(0.051)	(0.064)	(0.053)
log(POI income) × Rural MO	0.763***	0.968***	0.907***	0.919***	0.916***	0.724***	0.820***
	(0.113)	(0.109)	(0.122)	(0.120)	(0.117)	(0.142)	(0.127)
log(POI income) × Urban	0.184***	0.179***	0.180***	0.180***	0.259***	0.301***	0.263***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)	(0.021)	(0.018)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	61.28%	354.72%	278.86%	287.90%	103.61%	28.08%	65.15%

[a] Standard errors (clustered at census tract) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[b] Columns (1)–(4) are standard logit; columns (5)–(7) allow a random coefficient on scaled travel cost.
[c] Intermediate control variable rows omitted for space; full results available from the authors.

Table 6: BLP Demand Estimates: Subsample – Drop Population Groups with < 100 Annual Visits

	Logit (OLS)	Logit (IV)			RC Logit (IV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument Var.	–	500m	1000m	log(dist)	500m	1000m	log(dist)
EVCS within 500m	0.046***	0.283***	0.234***	0.232***	0.256***	0.171***	0.189***
	(0.012)	(0.051)	(0.049)	(0.042)	(0.045)	(0.046)	(0.038)
Travel cost (scaled)	−0.319***	−0.321***	−0.321***	−0.320***	−0.578***	−0.688***	−0.620***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.094)	(0.104)	(0.097)
$\sigma_{\text{travel cost}}$					0.362***	0.447***	0.396***
					(0.075)	(0.076)	(0.074)
log(POI income) × Rural MO	0.731***	0.938***	0.882***	0.891***	0.922***	0.811***	0.842***
	(0.115)	(0.111)	(0.123)	(0.121)	(0.111)	(0.125)	(0.121)
log(POI income) × Urban	0.188***	0.183***	0.184***	0.184***	0.223***	0.241***	0.231***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.017)	(0.018)	(0.017)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	57.45%	355.40%	293.73%	291.75%	178.94%	100.32%	122.44%

[a] Standard errors (clustered at census tract) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[b] Columns (1)–(4) are standard logit; columns (5)–(7) allow a random coefficient on scaled travel cost.
[c] Sample restriction drops all census tracts with fewer than 100 total visits in the year.
[d] Intermediate control rows omitted; full results available from the authors.

Table 7: BLP Demand Estimates: Subsample – Drop Population Groups with < 500 Annual Visits

	Logit (OLS)	Logit (IV)			RC Logit (IV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument Var.	–	500m	1000m	log(dist)	500m	1000m	log(dist)
EVCS within 500m	0.056***	0.310***	0.234***	0.241***	0.265***	0.125**	0.173***
	(0.014)	(0.058)	(0.056)	(0.046)	(0.050)	(0.051)	(0.041)
Travel cost (scaled)	−0.348***	−0.350***	−0.350***	−0.350***	−0.664***	−0.945***	−0.798***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.111)	(0.146)	(0.124)
$\sigma_{\text{travel cost}}$					0.410***	0.604***	0.507***
					(0.083)	(0.093)	(0.084)
log(POI income) × Rural MO	0.942***	1.168***	1.096***	1.122***	1.018***	0.760***	0.862***
	(0.145)	(0.135)	(0.156)	(0.152)	(0.142)	(0.194)	(0.173)
log(POI income) × Urban	0.236***	0.234***	0.235***	0.235***	0.281***	0.318***	0.300***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.019)	(0.021)	(0.019)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	59.68%	325.42%	245.81%	253.89%	146.72%	48.63%	79.61%

[a] Standard errors (clustered at census tract) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[b] Columns (1)–(4) are standard logit; columns (5)–(7) allow a random coefficient on scaled travel cost.

[c] Sample restriction drops all census tracts with fewer than 500 total visits in the year. Travel cost SD in this subsample is $\sigma_C = 12.512$.

Table 8: BLP Demand Estimates: Market Shares Divided by 2 (Outside Option Sensitivity Check)

	Logit (OLS)	Logit (IV)			RC Logit (IV)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Instrument Var.	–	500m	1000m	log(dist)	500m	1000m	log(dist)
EVCS within 500m	0.046***	0.278***	0.230***	0.229***	0.244***	0.153***	0.173***
	(0.012)	(0.050)	(0.048)	(0.041)	(0.044)	(0.045)	(0.037)
Travel cost (scaled)	−0.318***	−0.320***	−0.319***	−0.319***	−0.648***	−0.784***	−0.709***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.096)	(0.109)	(0.099)
$\sigma_{\text{travel cost}}$					0.394***	0.484***	0.436***
					(0.066)	(0.068)	(0.064)
log(POI income) × Rural MO	0.737***	0.943***	0.886***	0.896***	0.914***	0.789***	0.820***
	(0.114)	(0.110)	(0.123)	(0.120)	(0.112)	(0.127)	(0.122)
log(POI income) × Urban	0.187***	0.182***	0.183***	0.183***	0.232***	0.253***	0.242***
	(0.013)	(0.013)	(0.014)	(0.013)	(0.017)	(0.018)	(0.017)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	58.43%	349.62%	289.95%	288.32%	151.06%	78.17%	97.81%

[a] Standard errors (clustered at census tract) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[b] Columns (1)–(4) are standard logit; columns (5)–(7) allow a random coefficient on scaled travel cost.
[c] All market shares divided by 2, inflating the outside option share and testing sensitivity to its level.

Table 9: Logit Demand Estimates: 500m-Family IV Robustness (Main Share Definition)

	OLS	Logit IV Robustness					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oil-shock IV	–	Supply	Demand	Supply	Demand	Supply	Demand
Spatial IV	–	$n^{\text{roadden}}_{\text{ports},500m}$	$n^{\text{roadden}}_{\text{ports},500m}$	$\log(\text{dist}^{\text{popden}})$	$\log(\text{dist}^{\text{popden}})$	PeriphPortsAfter	PeriphPortsAfter
EVCS within 500m	0.046^{***}	0.284^{***}	0.282^{***}	0.187^{***}	0.185^{***}	0.378^{***}	0.377^{***}
	(0.012)	(0.089)	(0.089)	(0.068)	(0.068)	(0.078)	(0.078)
Travel cost (scaled)	-0.317^{***}	-0.317^{***}	-0.318^{***}	-0.317^{***}	-0.318^{***}	-0.319^{***}	-0.319^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
log(POI income) × Rural MO	0.728^{***}	0.920^{***}	0.919^{***}	0.844^{***}	0.843^{***}	0.989^{***}	0.989^{***}
	(0.115)	(0.115)	(0.115)	(0.134)	(0.134)	(0.130)	(0.130)
log(POI income) × Urban	0.186^{***}	0.181^{***}	0.181^{***}	0.183^{***}	0.183^{***}	0.179^{***}	0.179^{***}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	58.73%	360.10%	356.25%	236.45%	233.67%	476.59%	473.87%

[a] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard logit model throughout.
[b] The two instrument rows list, for each IV specification, the oil-shock shifter and the paired spatial IV.
[c] Intermediate control rows omitted for space. Full results available from the authors.

Table 10: Logit Demand Estimates: 1000m-Family IV Robustness

	OLS	Logit IV Robustness					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oil-shock IV	–	Supply	Demand	Supply	Demand	Supply	Demand
Spatial IV	–	$n^{\text{roadden}}_{1000m}$	$n^{\text{roadden}}_{1000m}$	$n^{\text{popden}}_{1000m}$	$n^{\text{popden}}_{1000m}$	PeriphPortsAfter	PeriphPortsAfter
EVCS within 500m	0.046^{***}	0.185^{***}	0.184^{***}	0.119	0.118	0.378^{***}	0.377^{***}
	(0.012)	(0.054)	(0.054)	(0.082)	(0.082)	(0.078)	(0.078)
Travel cost (scaled)	-0.317^{***}	-0.317^{***}	-0.318^{***}	-0.317^{***}	-0.318^{***}	-0.319^{***}	-0.319^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
log(POI income) × Rural MO	0.728^{***}	0.845^{***}	0.844^{***}	0.787^{***}	0.787^{***}	0.989^{***}	0.989^{***}
	(0.115)	(0.128)	(0.128)	(0.143)	(0.143)	(0.130)	(0.130)
log(POI income) × Urban	0.186^{***}	0.183^{***}	0.183^{***}	0.185^{***}	0.185^{***}	0.179^{***}	0.179^{***}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	58.73%	234.78%	232.90%	151.00%	149.06%	476.59%	473.87%

[a] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[b] Intermediate control rows omitted for space.

Table 11: Logit Demand Estimates: Log-Distance-Family IV Robustness

	OLS	Logit IV Robustness					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oil-shock IV	–	Supply	Demand	Supply	Demand	Supply	Demand
Spatial IV	–	$\log(\text{dist}^{\text{roadden}})$	$\log(\text{dist}^{\text{roadden}})$	$\log(\text{dist}^{\text{popden}})$	$\log(\text{dist}^{\text{popden}})$	PeriphPortsAfter	PeriphPortsAfter
EVCS within 500m	0.046^{***}	0.194^{***}	0.193^{***}	0.187^{***}	0.185^{***}	0.378^{***}	0.377^{***}
	(0.012)	(0.043)	(0.043)	(0.068)	(0.068)	(0.078)	(0.078)
Travel cost (scaled)	-0.317^{***}	-0.317^{***}	-0.318^{***}	-0.317^{***}	-0.318^{***}	-0.319^{***}	-0.319^{***}
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
log(POI income) × Rural MO	0.728^{***}	0.851^{***}	0.851^{***}	0.844^{***}	0.843^{***}	0.989^{***}	0.989^{***}
	(0.115)	(0.124)	(0.124)	(0.134)	(0.134)	(0.130)	(0.130)
log(POI income) × Urban	0.186^{***}	0.183^{***}	0.183^{***}	0.183^{***}	0.183^{***}	0.179^{***}	0.179^{***}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean WTP (% of travel cost)	58.73%	245.55%	244.28%	236.45%	233.67%	476.59%	473.87%

[a] Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[b] Intermediate control rows omitted for space.

Table 12: Reduced Form: OLS and IV Second Stage, County Fixed Effects

	Nearby IVs (rings)				Simulated: Road density			Simulated: Population density			Simulated: POI pop. density (tract)		
	OLS	IV (2–4km)	IV (3–5km)	IV (1–5km)	OLS	IV (500m)	IV (dist.)	OLS	IV (500m)	IV (dist.)	OLS	IV (500m)	IV (dist.)
travel_cost	−0.236***	−0.241***	−0.240***	−0.242***	−0.236***	−0.238***	−0.240***	−0.237***	−0.239***	−0.240***	−0.236***	−0.237***	−0.234***
	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)
log_poi_population	0.413***	0.456***	0.442***	0.466***	0.400**	0.388**	0.377**	0.363**	0.351**	0.346**	0.408***	0.411***	0.393***
	(0.130)	(0.135)	(0.131)	(0.139)	(0.159)	(0.158)	(0.162)	(0.159)	(0.160)	(0.160)	(0.131)	(0.130)	(0.138)
ug_Rural_MO_x_log_income	1.231***	1.196***	1.207***	1.188***	1.245***	1.220***	1.197***	1.252***	1.201***	1.182***	1.230***	1.229***	1.237***
	(0.170)	(0.206)	(0.185)	(0.225)	(0.172)	(0.172)	(0.173)	(0.163)	(0.166)	(0.170)	(0.169)	(0.168)	(0.179)
ug_Urban_x_log_income	0.858***	0.282	0.469**	0.145	0.902***	0.728***	0.573***	0.884***	0.552**	0.431**	0.865***	0.827***	1.053***
	(0.174)	(0.199)	(0.195)	(0.203)	(0.166)	(0.191)	(0.190)	(0.173)	(0.225)	(0.219)	(0.175)	(0.187)	(0.244)
have_EVCS_in_500m	0.518***	2.619***	1.936***	3.121***	0.480***	1.008***	1.482***	0.486***	1.392***	1.722***	0.501***	0.641**	−0.179
	(0.076)	(0.590)	(0.460)	(0.543)	(0.071)	(0.300)	(0.321)	(0.081)	(0.344)	(0.336)	(0.075)	(0.294)	(0.477)
First-Stage F	–	247.83	381.07	280.27	–	428.10	430.45	–	252.53	572.62	–	779.74	639.79
N	189,915	189,915	189,915	189,915	190,453	190,453	190,453	190,453	190,453	190,453	190,453	190,453	190,453

Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. Intermediate control rows omitted.

Table 13: Reduced Form: IV First Stage, County Fixed Effects

	Nearby IVs (rings)			Simulated: Road density			Simulated: Pop. density		Simulated: POI pop. density	
	IV (2–4km)	IV (3–5km)	IV (1–5km)	IV (500m)	IV (1km)	IV (dist.)	IV (500m)	IV (dist.)	IV (500m)	IV (dist.)
Instrument (Rural KS)	−0.006***	−0.011***	−0.005***	−0.110***	0.120***	0.001	−0.029***	0.157***	0.008***	−0.010
	(0.000)	(0.001)	(0.000)	(0.031)	(0.017)	(0.014)	(0.002)	(0.007)	(0.001)	(0.010)
Instrument (Rural MO)	0.030***	0.059***	−0.018***	0.566***	0.478***	−0.517***	0.043***	−0.288***	0.034***	−0.262***
	(0.010)	(0.018)	(0.005)	(0.033)	(0.051)	(0.034)	(0.008)	(0.030)	(0.002)	(0.034)
Instrument (Urban)	0.004***	0.005***	0.001**	0.288***	0.148***	−0.187***	−0.006**	−0.032*	0.017***	−0.261***
	(0.001)	(0.001)	(0.000)	(0.028)	(0.022)	(0.014)	(0.003)	(0.017)	(0.002)	(0.011)
Partial F-statistic	247.83	381.07	280.27	428.10	172.79	430.45	252.53	572.62	543.23	639.79
Partial R^2	0.0181	0.0453	0.0257	0.0159	0.0204	0.0356	0.0334	0.0666	0.0359	0.0472
N	189,915	189,915	189,915	190,453	190,453	190,453	190,453	190,453	190,453	190,453

Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$. Intermediate control rows omitted.